Evaluation of the SWAT Model's Sediment and Nutrient Components in the Piedmont Physiographic Region of Maryland

T. W. Chu, A. Shirmohammadi, H. Montas, A. Sadeghi

Abstract. *Mathematical watershed−scale models are among the best tools available for analyzing water resources (quantity and quality) issues in spatially diverse watersheds since continuous water quality monitoring is expensive and spatially impractical in mixed land use watersheds. However, models without appropriate validation may lead to misconceptions and erroneous predictions. This study used six years of hydrologic and water quality data to calibrate and validate the capability of SWAT (Soil and Water Assessment Tool) model in assessing nonpoint source pollution for a 346 ha watershed in the Piedmont physiographic region. The evaluation of the hydrology component of SWAT completed in a previous study pointed out that SWAT has no mechanism to account for subsurface flow contributions from outside the watershed. For this evaluation, all nutrient loadings leaving the watershed were adjusted to subtract the chemical transport via subsurface flow contributions from outside the watershed. Evaluation results indicated a strong agreement between yearly measured and simulated data for sediment, nitrate, and soluble phosphorus loadings. However, simulations of monthly sediment and nutrient loadings were poor. Overall, it was concluded that SWAT is a reasonable watershed−scale model for long−term simulation of different management scenarios. However, its use on storm−by−storm or even on monthly basis may not be appropriate for watersheds with similar physiography and size. Additionally, ignoring the subsurface contribution of water and chemicals from outside the watershed into the watershed aquifer could cause significant errors in model prediction.*

Keywords. *Nutrients, Sediment, SWAT model, Water quality, Watershed scale.*

Nonpoint source (NPS) pollution of streams, lakes, and estuaries has created a critical concern throughout the world. Agricultural activities have been identified as the primary sources of NPS pollutants (sediments, nutrients, pesticides). Although there are many potential contributors of nonpoint source pollution, including golf courses, urban development, and stream bank erosion, agriculture is the leading contributor of sediment and nutrients to streams and rivers in the U.S. (USEPA, 1998). Sediments in water bodies not only damage the recreational and aesthetic values of the water but also contribute major pollutants to surface water. Pollutants such as chemicals and pathogens may be transported both in solution and attached to sediments. According to the USDA−SCS (1989), soil erosion is the source of 99% of the total suspended solid loads in waterways in the U.S. Gianessi et al. (1981) reported that agricultural croplands and rangelands produce 62% of total annual suspended solids. Agriculture also accounts for 66% and 65% of the total national phosphorus and nitrogen discharges, respectively.

Agrochemicals and animal manures are extensively used in the U.S. to increase crop production, but their improper use may cause serious water quality problems in both surface and groundwater resources. For example, the application of nitrogen fertilizer to intensively cropped areas, and other crop management practices, provide a considerable source of nitrate that may move to stream flow through subsurface flow or leach deeper into the soil profile and reach the groundwater system in areas with vulnerable soils and hydrogeology. For the Chesapeake Bay, one of the world's largest estuaries, nonpoint sources of pollutants contribute approximately 67% of the nitrogen and 39% of the phosphorus that reach the bay (Angle et al., 1986). Estimates of nutrient inputs to the bay from the Maryland portion of its watershed attribute over 40% of the total phosphorus inputs to agricultural activities (Chesapeake Bay Program, 1988).

Continuous water quality monitoring is very expensive, time consuming, and spatially impractical at the watershed level. Therefore, mathematical modeling has become a primary technology for analyzing NPS pollution and its spatial distribution. Watershed−scale models that can be used to predict the effects that changes in agricultural activity have on runoff, soil erosion, and nutrient transport are essential to analyze nonpoint source pollution in agricultural watersheds. The use of watershed−scale models has also been proposed to aid in the development of total maximum daily load (TMDL). Since measured data are often insufficient to thoroughly depict pollution levels within a watershed, models would be used to assess the pollutant loadings

Article was submitted for review in December 2003; approved for publication by the Soil & Water Division of ASAE in July 2004.

The authors are **Tzyy−Woei Chu, ASAE Member Engineer,** Post−Doctoral Research Associate, **Adel Shirmohammadi, ASAE Member Engineer,** Professor, and **Hubert J. Montas, ASAE Member Engineer,** Associate Professor, Department of Biological Resources Engineering, University of Maryland, College Park, Maryland; and **Ali M. Sadeghi, ASAE Member Engineer,** Soil Physicist, USDA−ARS Environmental Quality Laboratory, Beltsville, Maryland. **Corresponding author:** Adel Shirmohammadi, Department of Biological Resources Engineering, University of Maryland, College Park, MD 20742−5711; phone: 301−405−1185; fax: 301−314−9023; e−mail: as31@umail.umd.edu.

allowed to be discharged into the receiving waterbody and in allocating pollutant loads between point and nonpoint sources.

Without proper validation, watershed−scale models may lead to erroneous predictions. However, model validation is often a difficult proposition because of the lack of long−term watershed monitoring data. This study continues the effort for evaluating the SWAT (Soil and Water Assessment Tool) model with measured data, initiated by Chu and Shirmohammadi (2004) where the hydrology component was validated. Six years of hydrologic and nutrient loading data were used to evaluate the sediment and nutrient components of SWAT over a 346 ha watershed in the Piedmont physiographic region of Maryland.

In general, applications of SWAT for assessing NPS pollution have shown reasonable results. Bingner et al. (1997) evaluated the effect of watershed subdivision on SWAT simulation of runoff and fine sediment yield. They reported that annual fine sediment yield produced from uplands was very sensitive to the level of watershed subdivision, while annual runoff was not sensitive. The results also indicated that SWAT underestimated the total annual fine sediment yield produced from all sediment sources within the Goodwin Creek watershed in northern Mississippi.

Srinivasan et al. (1998) reported the application of SWAT to Richland and Chambers Creeks watershed in the upper Trinity River basin in Texas. Their findings revealed a relatively wide range for Nash−Sutcliffe coefficient (R^2) values (0.52 to 0.84), when comparing the simulation results to the observed monthly stream flow during both calibration and validation phases of the model assessment. In addition, SWAT estimated the accumulated sediment loadings over 3 to 7 year periods within 2% and 9% of the measured data during both calibration and validation phases of the model, respectively. Kirsch (2000) and Kirsch et al. (2002) used SWAT to predict flow, sediment, and phosphorus loads for the Rock River basin in southern Wisconsin. Two subareas (Jackson Creek and Yahara River) were selected for verifying SWAT's capability before applying it to entire basin. The results revealed R^2 values of annual flow, sediment, and phosphorus to be 0.41, −1.64, −1.37 for Jackson Creek and 0.61, 0.75, 0.07 for Yahara River, respectively. Kirsch also indicated that SWAT was less accurate during years with high runoff.

Saleh et al. (2000) applied SWAT to assess the effect of dairy production on water quality within the upper North Bosque River watershed of north central Texas. Model outputs were compared to flow, sediment, and nutrient measurements for 11 stream sites within the watershed for the period of October 1993 to July 1995. Daily flow, sediment, and nutrient loading from the dairy waste application fields were simulated in the APEX (Agricultural Policy/Environmental eXtender) model (Williams et al., 1998) and then input into SWAT as direct point sources. The results indicated that SWAT was able to predict the average monthly flow, sediment, and nutrient loadings (organic N, NO_3−N, organic P, PO_4−P) at 11 stream sites reasonably well, with R^2 values ranging from 0.65 to 0.99. Average monthly flow and loadings for the entire watershed were also adequately simulated, with R^2 values ranging from 0.54 to 0.94, except for NO_3−N with an R^2 value of 0.27. Saleh et al. (2000) reported that the predicted organic N, organic P, and PO_4−P were generally close to or slightly lower than the measured values, while NO_3−N was overpredicted by SWAT at all sites on a monthly basis.

Santhi et al. (2002) applied SWAT to demonstrate the advantage of a model in a TMDL development process for estimating phosphorus loadings under existing and projected conditions of the watershed. They also analyzed the effectiveness of various phosphorus control BMPs in the Bosque River watershed in Texas. Measured flow, sediment, organic nitrogen, mineral nitrogen, and phosphorus on a monthly basis from 1993 through 1998 were used in model calibration. Results indicated that simulated monthly flow, sediment, and nutrient loadings were close to the observed values during the calibration period (Santhi et al., 2001). The calibrated model was then applied to quantify the effects of BMPs related to dairy manure management and municipal wastewater treatment plant effluent. The results revealed that dairy management measures had greater benefit in reducing loadings (mass) of soluble P than soluble P concentrations. However, wastewater treatment plant (WWTP) scenarios showed greater benefit in reducing soluble P concentrations than total P loadings.

MATERIALS AND METHODS

DESCRIPTION OF STUDY SITE

The selected 346 ha Warner Creek watershed, located in the Piedmont physiographic region of Maryland (39° 35′ 3″ latitude, 77° 14′ 31.5″ longitude at the outlet of watershed), is part of the NPS−319 project in the Monocacy River watershed. The watershed drains into Little Pipe Creek and then into the Monocacy River. These water bodies are part of the Chesapeake Bay watershed. According to a USDA report (USDA−SCS, 1990), the Monocacy River has been ranked as number 3 among 30 priority river basins regarding the potential release of phosphorus to Chesapeake Bay, and as number 20 regarding the potential release of nitrogen. This watershed was selected for study considering land use characteristics, hydrologic characteristics and stream conditions, BMP implementation plans, and cooperative characteristics of the farmers (Shirmohammadi et al., 1997). A series of monitoring stations was established along Warner Creek to collect hydrologic parameters and water quality samples. The location of the watershed and the distribution of monitoring stations are shown in figure 1. However, only data collected at station 2A (outlet of the watershed) were used in this study.

In the Warner Creek watershed, the two dominant soil types are Manor−Edgemont−Brandywine soils and Penn−Readington−Croton soils. The Penn soils are drained somewhat excessively, the Readington soils are drained moderately well, and the Croton Soils are drained poorly. Approximately 65% of the land surface has been classified as moderately erodible, while 12% has been classified as severely erodible (USDA−SCS, 1960). In general, most of the upland agricultural soils belong to the Penn silt loam series with an average slope of 3% to 8%. Land use in the watershed includes a mixture of dairy, beef, pasture, and cropland. There are three major dairy operations, totaling to about 620 heads of milking cows. A more intense portion of the dairy operation is located in the upper portion of the watershed (subwatershed 1B) involving 270 heads of dairy cows in 80 ha.

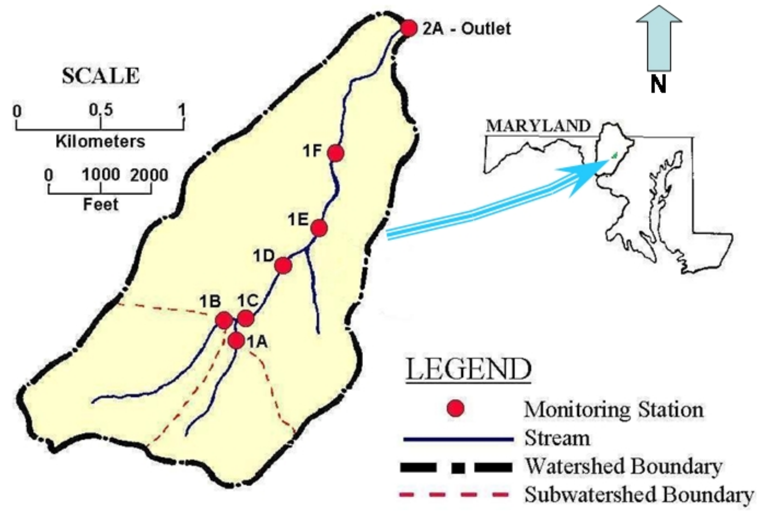

Figure 1. Location and monitoring set up for Warner Creek watershed, Frederick County, Maryland.

DATA ACQUISITION

Watershed information such as soils, topography, and land use were recorded by the ERDAS IMAGINE geographic information system (Searing and Shirmohammadi, 1994). Using SPOT satellite images, USGS 7′ quad−sheets, and the Global Positioning System (GPS), the entire watershed topography and boundary data were electronically recorded in the ERDAS IMAGINE GIS system. The soil database was extracted from the USDA Soil Conservation Service's state soils map. Land use data has been collected on each tract of land and stored in the GIS system for every field identified by aerial photos obtained from the USDA−ASCS office.

Station 2A was gauged and equipped with a continuous recording automatic ISCO flowmeter and sampler. Rainfall data were measured using a continuous recording rain gauge near station 2A, and these data were supplemented by daily readings of a manual rain gauge at the same station. The sampling scheme applied to all stations (1A, 1B, 1C, and 2A) involved grab sampling on weekly intervals from February through June and biweekly for the rest of the year. The automated system measured and sampled the storm events that occurred between the regular grab sampling times at the outlet of the watershed (station 2A). This selected frequency provided a reasonable trend in hydrologic and water quality response of the watershed and satisfied the EPA's national monitoring guidelines (USEPA, 1991). Water samples were analyzed for sediment, ammonia nitrogen, nitrite nitrogen, nitrate nitrogen, total Kjeldahl nitrogen (TKN), total phosphorus, and ortho−phosphate. An automated ion analyzer (Lachat model 1000−1) was used to analyze the nutrient samples. The Quickchem methods (reaction modules) used with the automated ion analyzer for the constituents of interest are EPA approved. Crop management, farm fertilization habits, and manure applications were recorded by the Monocacy Watershed Project Office (Burdette, 1996).

MODEL BACKGROUND

Arnold et al. (1993) developed the SWAT model to assist water resource managers in assessing the impact of management on water supplies and nonpoint source pollution in watersheds and large river basins on a long−term basis. SWAT is a modified version of the SWRRB (Simulator for Water Resources in Rural Basins) model (Arnold et al., 1990). The major changes to SWRRB include: (1) expanding the ability of computation on hundreds or thousands of grid cells or subwatersheds, (2) adding lateral subsurface flow and groundwater flow components, and (3) modifying the routing structure, irrigation and water transfer through ponds, reservoirs, and channel reaches.

SWAT is a complex, physically based model with a spatially explicit parameterization capability. A complete description of SWAT's components is found in Arnold et al. (1998). In brief, SWAT is a continuous simulation model and operates on a daily time step to perform simulations up to 100 years using measured and/or stochastically generated weather data. The major components of SWAT model include hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, agricultural management, channel routing, and reservoir routing. Detailed description of each component is provided in Arnold et al. (1998). For the purposes of this study, a brief background on the sediment and nutrient components are provided below.

SWAT Sediment

The SWAT model estimates soil erosion and sediment yield from the landscape and in−stream depositional and degrading processes. The sediment yield from the landscape is calculated by the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975). Sediment deposition and degradation in the stream channel are both calculated during the sediment routing. The maximum amount of sediment that can be transported from a reach segment during channel sediment routing is determined by the modified Bagnold's equation (Bagnold, 1977):

$$CONC_{sed,ch,mx} = SPCON \times V_c^{SPEXP} \quad (1)$$

where $CONC_{sed,ch,mx}$ is the maximum concentration of sediment that can be transported (ton/m^3 or kg/L), SPCON is the coefficient in this equation defined by the user, V_c is the peak flow velocity (m/s) in the channel, and SPEXP is an exponent parameter in the equation. The coefficient (SPCON) should be between 0.0001 and 0.01. The exponent (SPEXP) normally ranges from 1.0 to 2.0.

SWAT Nutrients

Nitrogen and phosphorus processes in the SWAT model are handled in a similar manner as in the Erosion Productivity Impact Calculator (EPIC) model (Williams, 1990, 1995). The amount of nitrate nitrogen in runoff is only considered in the top soil layer (10 mm thickness). Nitrate−N loading is estimated as the product of the volume of runoff and nitrate concentration in the first layer. Amounts of NO_3−N contained in lateral subsurface flow and percolation are estimated as products of the water volume and the average concentration of nitrate in each layer. Organic N transport with sediment is calculated with a loading function developed by McElroy et al. (1976) and modified by Williams and Hann (1978). The loading function estimates the daily organic N runoff loss based on the concentration of organic N in the top soil layer, the sediment yield, and the enrichment ratio. The enrichment ratio is the ratio of the mass of organic nitrogen in the sediment to that in the soil. In addition, the plant uptake of nitrogen is estimated using a supply−and−demand approach.

Because phosphorus is not very soluble, phosphorus loss in surface runoff is calculated based on the similar concept of partitioning pesticides into the solution and sediment phases, as described by Leonard and Wauchope (1980). The amount of soluble phosphorus removed in runoff is predicted using the labile P concentration in the top 10 mm of the soil, the runoff volume, and a partitioning factor. Sediment transport of P (particulate P) is simulated by a loading function, as described in organic N transport. Phosphorus used by the crop is also estimated with the supply−and−demand approach.

SWAT adopted a modified version of the QUAL2E model (Brown and Barnwell, 1987) to simulate in−stream nutrient transformations. QUAL2E is intended for use as a water quality planning tool, which can be operated as a steady−state or as a dynamic model. The sub−components of QUAL2E include models of the biochemical dynamics of algae as chlorophyll−*a*, dissolved oxygen, carbonaceous oxygen demand, organic nitrogen, ammonium nitrogen, nitrite nitrogen, nitrate nitrogen, organic phosphorus, and soluble phosphorus.

Model Evaluation Methods

Statistical Methods

Graphical methods (time series plot and scattergram) and statistical measures were used to evaluate the model performance based on the measured data. Four statistical criteria were used to evaluate the hydrologic goodness of fit: the correlation coefficient (r), the coefficient of determination (r^2), the Nash−Sutcliffe coefficient (R^2) (Nash and Sutcliffe, 1970), and the root mean square deviation (RMS). The correlation coefficient (r) is an index of the degree of linear association between the observed and simulated values, with zero indicating no linear relationship and extreme values (1.0 and −1.0) indicating positive and negative relationships, respectively. Its square (r^2) represents the percentage of variance in the measured data that is explained by the simulated data. If the r^2 value is equal to zero, there is no incentive to use two regression parameters to summarize the data. The Nash−Sutcliffe coefficient (R^2), also called the coefficient of efficiency, indicates how well the plot of observed versus simulated data is close to the 1:1 (equal value) line. The Nash−Sutcliffe coefficient is similar to the coefficient of determination. However, R^2 compares the observed values to the 1:1 line of measured versus predicted data instead of the linear regression line of best−fit. The R^2 value is calculated as:

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \overline{O})^2 - \sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \quad (2)$$

where O_i and P_i are the observed and predicted values, respectively, $\overline{O}$ is the mean of the observed values, and n is the number of samples. The R^2 value can range from $-\infty$ to 1, with 1 indicating a perfect fit and negative values being typical of significant errors in mean predictions.

Another goodness−of−fit criterion is root mean square deviation (RMS). It is equal to the square root of the variance. The smaller the RMS, the better the performance of the model, and a value of 0.0 for RMS represents perfect simulation of observed volume. The RMS value is given by:

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \quad (3)$$

where the parameters O_i, P_i, and n are defined as before.

Sensitivity Analysis

Sensitivity analysis is a technique for assessing the comparative change in model response resulting from a change in model inputs. It helps to identify the parameters that affect the model's output significantly. Identification of sensitive input parameters may help the modeler to adjust those parameters during model calibration. Only limited information on the sensitivity analysis of the SWAT model's input parameters has been reported. Spruill et al. (2000) indicated that the most sensitive parameters of the SWAT model for application in a central Kentucky watershed were saturated hydraulic conductivity, alpha base flow factor, drainage area, channel length, and channel width. Vandenberghe et al. (2001) applied the Latin Hypercube Sampling technique to investigate the parameter sensitivity for the in−stream water quality model (QUAL2E model) implemented in SWAT. The results showed that parameters related to the growth and the die−off of algae, BOD decay constant, and the benthic oxygen demand had significant effects on model predictions. The parameters selected from the SWAT model for sensitivity analysis in this study are based on literature references, personal judgments, and suggestions in SWAT's user manual. The selected parameters are summarized in table 1.

Sensitivity analysis provides a guide to decide which input parameters will have the significant impact on model prediction. There are a variety of ways to implement the sensitivity analysis. An expression of sensitivity called "condition number" (Chapra, 1997) is used in this study. Consider c as a function of each of the model parameters and forcing functions: that is, $c = f(k1, k2, k3, ...)$. The condition number can be expressed as:

$$CN_k = \frac{k}{c}\frac{\partial c(k)}{\partial k} \quad (4)$$

Table 1. The selected model parameters in the sensitivity analysis.

Input Parameter	Definition
Nitrogen	
BIOMIX	Biological mixing efficiency
NPERCO	Nitrogen percolation coefficient
AI1	Fraction of algal biomass that is nitrogen (mg N/mg algae)
K_N	Michaelis−Menton half−saturation constant for nitrogen (mg N/L)
P_N	Algal preference factor for ammonia
ORGANICN	Initial organic nitrogen concentration in the reach (mg organic N−N/L)
RS4	Rate coefficient for organic N settling in the reach (day^{-1})
BC2	Rate constant for biological oxidation of NO_2 to NO_3 in the reach (day^{-1})
Phosphorus	
BIOMIX	Biological mixing efficiency
PPERCO	Phosphorus percolation coefficient
PHOSKD	Phosphorus soil partitioning coefficient
UBP	Phosphorus uptake distribution parameter
AI2	Fraction of algal biomass that is phosphorus (mg P/mg algae)
K_P	Michaelis−Menton half−saturation constant for phosphorus (mg P/L)
RS2	Benthic (sediment) source rate for dissolved phosphorus in the reach (mg dissolved P/(m^2 day)
RS5	Organic phosphorus settling rate in the reach (day^{-1})
BC4	Rate constant for mineralization of organic P to dissolved P in the reach (day^{-1})
DISOLVP	Initial dissolved phosphorus concentration in the reach (mg soluble P−P/L)

where CN_k is defined as the condition number for the parameter k. If the derivative form is difficult to obtain, a discrete form is used for the derivative:

$$CN_k = \frac{k}{c}\frac{\Delta c}{\Delta k} \tag{5}$$

where

$$\frac{\Delta c}{\Delta k} = \frac{c(k+\Delta k) - c(k-\Delta k)}{2\Delta k} \tag{6}$$

The condition number provides a transfer function to propagate the relative error of the parameter into the relative error of the prediction. The bigger the condition number, the more sensitive the parameter is for the specific model prediction. A negative condition number indicates that the parameter has an opposite effect on prediction.

Previous Validation of Hydrology Component

The evaluation of the hydrology component of SWAT completed in the previous study (Chu and Shirmohammadi, 2004) pointed out subsurface flow contributions from outside the watershed. A simple water budget analysis was conducted to quantify the possible subsurface flow contribution from outside the watershed. A simple balance equation that contains basic elements of the water budget was used:

$$Pre + GI = SR + B + ET \pm \Delta S_s \pm \Delta S_g \tag{7}$$

where *Pre* is precipitation (mm), *GI* is groundwater inflow including seepage losses (mm), *SR* is surface runoff (mm), *B* is base flow (mm), *ET* is evapotranspiration (mm), ΔS_s is change in soil moisture (mm), and ΔS_g is change in groundwater storage (mm).

The major component of the incoming water is from precipitation (*Pre*). The groundwater inflow (*GI*) to the watershed was initially assumed to be zero. The outgoing water components are the surface runoff (*SR*), base flow (*B*), and evapotranspiration (*ET*). Precipitation was measured with a rain gauge within the watershed. Surface runoff and base flow were separated from streamflow, which was measured at the outlet of the watershed (station 2A). The actual evapotranspiration was estimated by the SWAT model due to the lack of observed data. The change in soil moisture (ΔS_s) was assumed to be zero on a long−term basis. The change in groundwater storage (ΔS_g) was estimated from the gravity yield (Y_g) of the watershed (Arnold and Allen, 1996) and the change in groundwater stage (ΔH). Change in groundwater stage was obtained from a water−level observation well located at 0.8 km west of Mount Airy (18 km from the upper boundary of watershed) in Frederick County, Maryland. The change in groundwater storage is:

$$\Delta S_g = \Delta H \times Y_g \tag{8}$$

where Y_g is described by equation 9 as:

$$Y_g = \frac{Pre - SR - B - ET}{\Delta H} \tag{9}$$

where all the parameters are defined before. The gravity yield value was taken from the Maryland Geological Survey reported for several of the Frederick County basins in Maryland (Duigon and Dine, 1987). Since there is no survey within the Warner Creek watershed, the average gravity yield value of similar regions (Y_g = 0.063) was used. The remaining component of the outgoing water is seepage loss to the deep aquifer or subsurface flow recharge from outside of the watershed. Because the groundwater inflow was assumed to be zero initially, the seepage loss could be considered as subsurface flow contribution from outside the watershed if its value is negative. The resulting values of seepage loss were found to be negative for each year in this study, thus indicating subsurface flow contributions from outside the watershed. Measured base flow was therefore corrected for the extra subsurface flow contribution from outside the watershed using the water balance adjustment. The corrected datasets from the water balance adjustment were used to obtain an objective evaluation of the SWAT model's performance. Detailed discussion can be found in Chu and Shirmohammadi (2004).

Approach for Model Calibration and Validation

The entire Warner Creek watershed was subdivided into 40 subwatersheds based on similarity of land use to allow consideration of significant spatial detail. The land use type and topography of each subwatershed were both extracted from the GIS database (Searing and Shirmohammadi, 1994). Soil parameters for the corresponding soil series extracted from the GIS system were obtained from the Soils−5 database contained in SWAT (Arnold et al., 1996). Site−measured daily rainfall data were used for entire watershed simulation, while missing data were filled using data from the Emmitsburg, Maryland weather station, located 11.5 km from the watershed. Measured daily maximum and minimum temperatures were also obtained from the Emmitsburg station and applied to the entire watershed. For divided subwatersheds

Table 2. Condition numbers of selected parameters in the nitrogen component of the SWAT model.

Parameter	Condition Number by Model Prediction					
	Organic N	NO_3−N in Surface Water	NO_3−N in Lateral Subsurface Flow	Plant Uptake N	NO_3−N Leached from the Soil Profile	Fresh Organic to Mineral N
BIOMIX	−0.165	−0.069	−0.014	−0.001	−0.024	−0.006
NPERCO	−0.003	0.966	0.056	0	−0.029	0

containing no channel reach, a wide and short imaginary channel was created (10 × 5 m) to aggregate surface runoff for channel routing. Monthly streamflows measured at the watershed outlet (station 2A) for the period of April 1994 through December 1999, which was separated into storm flow and base flow, were used for flow calibration and validation of the model simulations. In addition, average pollutant concentrations measured at the watershed outlet (station 2A), were used to calculate the pollutant loadings leaving the watershed. Flow data for 1998 were incomplete due to equipment malfunction; thus, a neural network approach (ASCE, 2000a, 2000b) was used to generate the flow data for this year using flow and rainfall data for the period of 1994 through 1997 and 1999.

The measured sediment loading for the entire watershed was estimated as the product of the measured flow volume and the sediment concentration at station 2A. Monthly measured sediment loadings from 1994 to 1995 were used for model calibration, while data from 1996 to 1997 were used for model validation. Visual inspection of time series plots and four statistical measures (r, r^2, R^2, and RMS) were used to evaluate the model's performance in sediment yield prediction during both calibration and validation periods.

Nutrients of interest in the SWAT model's prediction are nitrate nitrogen (NO_3−N), ammonia nitrogen (NH_4−N), total Kjeldahl nitrogen (TKN), soluble phosphorus (PO_4−P), and total phosphorus (TP). Because of the presence of subsurface flow contribution from outside the watershed boundary (Chu and Shirmohammadi, 2004), all nutrient loadings leaving the watershed were adjusted to subtract the chemical transport via subsurface flow contribution from outside the watershed. This process permits a fair evaluation of the nutrient component of the SWAT model, especially for small watersheds such as the one in this study. The total nutrient loading is the summation of loading from both surface runoff and base flow. The base flow loading was therefore modified by equation 10:

$$\mathrm{NLOAD}' = \mathrm{NLOAD} \times \frac{B_i'}{B_i} \tag{10}$$

where NLOAD is the monthly nutrient loading (kg/ha), NLOAD′ is the monthly nutrient loading after adjustment (kg/ha), B_i is the monthly measured base flow (mm), and B_i' is the monthly base flow after subtracting the contribution from outside of the watershed (mm).

Measured monthly nitrate loadings from April 1994 through December 1995 were used for nitrate calibration, while the remaining data (1996 through 1999) were used for nitrate validation. Once the nitrate calibration was complete, the measured monthly data from April 1994 through December 1999 were used for ammonia and TKN validation. For TKN validation, the summation of simulated ammonia and organic nitrogen was compared to measured TKN data.

The simulated soluble phosphorus was compared to measured ortho−phosphate, while the summation of simulated soluble and organic phosphorus was compared to measured total phosphorus loading. Measured monthly ortho−phosphate loadings from April 1994 through December 1996 were used for soluble phosphorus calibration. The remaining data (1997 through 1999) were used for model validation. After soluble phosphorus calibration was done, the measured data for the entire period (April 1994 through December 1999) were used for total phosphorus validation.

Results and Discussion

Sensitivity Analysis

Table 2 shows the condition number of selected parameters for SWAT's nitrogen simulation. Predictions of nitrate in surface runoff are very sensitive to the NPERCO parameter (nitrogen percolation coefficient), while nitrate in lateral subsurface flow is only moderately sensitive to this parameter. Organic nitrogen production is moderately sensitive to the BIOMIX parameter (biological mixing efficiency), and this parameter slightly affects nitrate in surface runoff and lateral subsurface flow. It is notable that increases in BIOMIX have a negative effect on the six model predictions from their negative condition numbers. Parameters AI1, K_N, and P_N in the general water quality input file (.wwq file) and parameters ORGANICN, RS4, and BC2 in the stream water quality input file (.swq file) had no effect on the nitrogen simulations. Those parameters are related to the nitrogen transformation and transport in stream. Their associated condition numbers for the six nitrogen related predictions are all zero.

The condition numbers of selected parameters in the phosphorus submodel are presented in table 3. Soluble phosphorus in surface runoff is more sensitive to BIOMIX than organic phosphorus bound to sediment, considering the condition numbers of −0.233 and −0.035, respectively. PPERCO (phosphorus percolation coefficient) has a moder−

Table 3. Condition numbers of selected parameters in the phosphorus component of the SWAT model.

Parameter	Condition Number by Model Prediction						
	Organic P with Sediment	Soluble P in Surface Runoff	Plant Uptake P	Active to Labile P	Active to Stable P	Stable Organic to Active Organic P	Fresh Organic to Mineral P
BIOMIX	−0.035	−0.233	0	0.008	0.007	0.168	−0.005
PPERCO	0.003	0.235	0	−0.008	−0.008	−0.003	0
PHOSKD	0.0004	−0.975	0	0.035	0.035	0	0
UBP	−0.008	−0.165	0	−0.009	−0.023	0.001	0

Table 4. Default and final calibrated values of parameters used in nutrient calibration.

Nutrient	Parameter	Range	Model Default Value	Calibrated Value
Nitrogen	BIOMIX	0.0−1.0	0.20	0.21
	NPERCO	0.0−1.0	0.20	0.22
Phosphorus	BIOMIX	0.0−1.0	0.20	0.21
	PPERCO	10.0−17.5	10.0	10.0
	PHOSKD	100.0−200.0	175.0	200.0
	UBP	0.0−100.0	20.0	18.0

ate effect on soluble P in surface runoff (CN = 0.235) but little influence on organic P (CN = 0.003). Soluble P in surface runoff was highly sensitive to PHOSKD (phosphorus soil partitioning coefficient), with a CN of −0.975. However, PHOSKD has nearly no effect on organic P, with a CN of 0.0004. The UBP (phosphorus uptake distribution) parameter shows only moderate effect on soluble P, with a CN of −0.165 and low sensitivity to organic P with a CN of −0.008. It was also found that phosphorus predictions are not sensitive at all to parameters AI2 and K_P in the .wwq file and RS2, RS5, BC4, and DISOLVP in the .swq file, thus registering zero condition numbers. Similar results on the lack of effects of the latter parameters in SWAT were reported by Houser and Hauck (2002). These authors' results, the present results, and the QUAL2E results of Vandenberghe et al. (2001) discussed earlier suggest a possible mis−implementation of QUAL2E equations in the SWAT model. Alternatively, the scale of the present watershed may simply be too small for in−stream processes to be significant in comparison with overland and subsurface processes.

Model Calibration

Parameters that affect the sediment yield and transport were calibrated until the simulated monthly sediment yield closely matched the observed data. The control practice factor (PE) in MUSLE was estimated based on the various subwatershed conditions, and its values ranged from 0.37 to 0.6. The soil erodibility factor (K) was adjusted to 0.28, 0.32, 0.37, 0.24, and 0.37 for the Penn, Manor, Croton, Linganore, and Readington soils, respectively. The crop management factor (C) was calculated by the model for all days when runoff occurred. Six input parameters were calibrated for the sediment routing process. CH_EROD (channel erodibility factor) and CH_COV (channel cover factor) were set from 0 to 0.32 and 0 to 0.3, respectively, according to the channel condition in each subwatershed. The peak rate adjustment factor (APM) for sediment routing in each subwatershed was set to 1.5 to adjust the effect of peak flow rate on sediment routing, while the peak rate adjustment factor (PRF) for sediment routing in the channel was set to 1.3. In addition, the resultant values of the SPCON and SPEXP factors (defined in eq. 1) after calibration were 0.0012 and 1.0, respectively.

For calibration of the nitrogen component, two parameters, nitrogen percolation coefficient (NPERCO) and biological mixing efficiency (BIOMIX), were adjusted to give a best match with the measured nitrate loadings. After nitrate calibration, no calibration was performed for ammonia and organic nitrogen since the two parameters were fixed. The nitrogen percolation coefficient controls the amount of NO_3−N removed from the surface layer in runoff relative to the amount removed via percolation. The final values of calibrated parameters are listed in table 4. Nitrogen transformation related parameters in the .wwq file (AI1, K_N, and P_N) and the .swq file (ORGANICN, RS4, and BC2) were found to have no effect on simulation according to the previous sensitivity analysis.

The phosphorus percolation coefficient (PPERCO), the phosphorus soil partitioning coefficient (PHOSKD), and the phosphorus uptake distribution parameter (UBP) were adjusted for soluble phosphorus calibration according to the sensitivity analysis results (table 3). The phosphorus percolation coefficient, similar to NPERCO, defines the ratio of the amount of soluble P removed from the surface layer in runoff relative to the amount of soluble P removed via percolation. The phosphorus soil partitioning coefficient is the ratio of phosphorus attached to sediment to phosphorus dissolved in soil water. The final values of those calibrated parameters are included in table 4. Similar to the nitrogen component, the phosphorus transformation related parameters in the .wwq file (AI2 and K_P) and the .swq file (DISOLVP, RS2, RS5, and BC4) had no effect on model prediction.

Hydrology

Figure 2 shows the time series plot of measured and simulated total streamflow during the calibration period. The corrected measured total streamflow at the outlet of the watershed (station 2A) was obtained by adding the surface runoff to the adjusted base flow for each event. Measured base flow was corrected for the extra subsurface flow contribution from the water balance adjustment. The model's simulation matches fairly well with measured data except in winter and

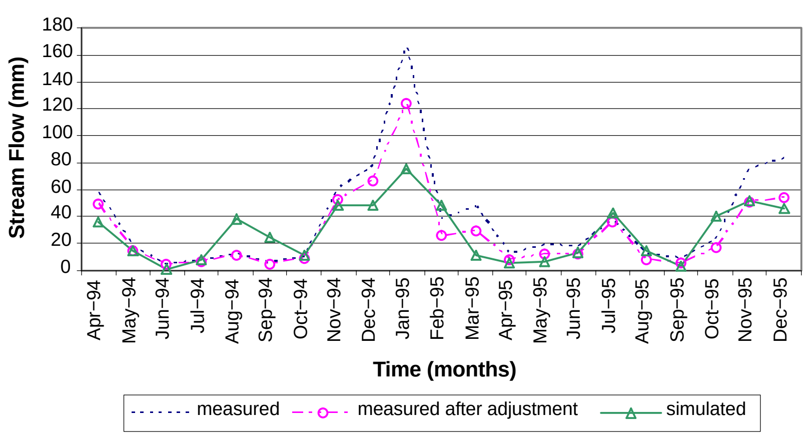

Figure 2. Time series plot of measured and simulated monthly streamflow (mm) data after adjustment during the calibration period (April, 1994−1995).

Table 5. Linear regression comparison and Nash−Sutcliffe coefficient for measured flow before and after adjustment versus simulated flow during calibration and validation periods.

Hydrologic Measurements	Intercept	Slope	r^2	R^2 (Nash−Sutcliffe)
Calibration period (April, 1994−1995)				
Base flow before adjustment	5.62	0.35	0.56	0.27
Base flow after adjustment	5.27	0.54	0.57	0.53
Streamflow before adjustment	11.47	0.44	0.66	0.52
Streamflow after adjustment	10.99	0.59	0.69	0.68
Validation period (1996−1999)				
Base flow before adjustment	11.67	0.53	0.47	0.42
Base flow after adjustment	13.63	0.78	0.42	−0.02
Streamflow before adjustment	11.20	0.61	0.69	0.63
Streamflow after adjustment	13.24	0.76	0.68	0.67
Validation period (1997−1999)				
Base flow before adjustment	6.15	0.64	0.62	0.60
Base flow after adjustment	5.92	0.82	0.66	0.62
Streamflow before adjustment	5.10	0.67	0.75	0.70
Streamflow after adjustment	5.35	0.78	0.78	0.78

early spring. Results indicate that the model's inability to simulate the extreme storm events was inherited from the weakness of the SCS curve number method for estimating surface runoff. However, the adjustments made to account for the subsurface flow recharge from outside the watershed improved the model's performance.

Table 5 shows the intercept, slope, and r^2 values of linear regression models and the Nash−Sutcliffe coefficient relating SWAT's simulations of base flow and streamflow to measured data for before and after flow adjustments. For most of the conditions, the increased regression slopes, r^2, and R^2 values indicate that flow adjustments resulted in a better agreement between measured data and model simulations, except for the extreme hydrologic year (1996). The significant improvement of the model's performance by excluding the abnormally wet year (1996) during the validation period was revealed in the increased values of R^2 (table 5), from −0.02 to 0.62 for base flow, and from 0.67 to 0.78 for streamflow, respectively. It may be concluded that SWAT was unable to simulate extremely wet hydrologic conditions. In addition, it should be noted that ignoring the subsurface contribution of water from outside the watershed into the watershed aquifer could cause significant errors in model predictions, especially for small watersheds. Complete discussion of the model performance can be found in Chu and Shirmohammadi (2004).

Sediment

Figure 3 shows the time series plot of measured and simulated monthly sediment loading during calibration. The trend of simulation basically follows the measured data, except for a large discrepancy in January 1995. The underestimated sediment yield in January 1995 could partially be attributed to the underestimated stream flow. However, the measured sediment yield in January 1995 was 3996 kg/ha, almost four times larger than the second largest monthly loading of April 1994 (fig. 3). In addition, comparing the highest stream flow (338 mm) in January 1996 with a sediment yield of 408 kg/ha, the stream flow of 166 mm in January 1995 was believed to be unreasonable to produce sediment yield of 3890 kg/ha. The average sediment concentration in January 1995 is almost 19 times larger than that in 1996. The abnormally high value could be attributed to potential measurement errors or the unexpected application of deicer by the county on the county road. Therefore, this unusually high value in January 1995 was considered an outlier due to the observation of deicer application on the county road and was excluded from statistical analysis. The reasoning for such exclusion was that this incident was not part of normal watershed management.

Table 6 provides the statistical results comparing the model simulations with measured data for the calibration and validation periods. The average concentration in April 1994 (1696 mg/L) is almost 14 times larger than that in January 1996 (120 mg/L). However, the resulting abnormally high

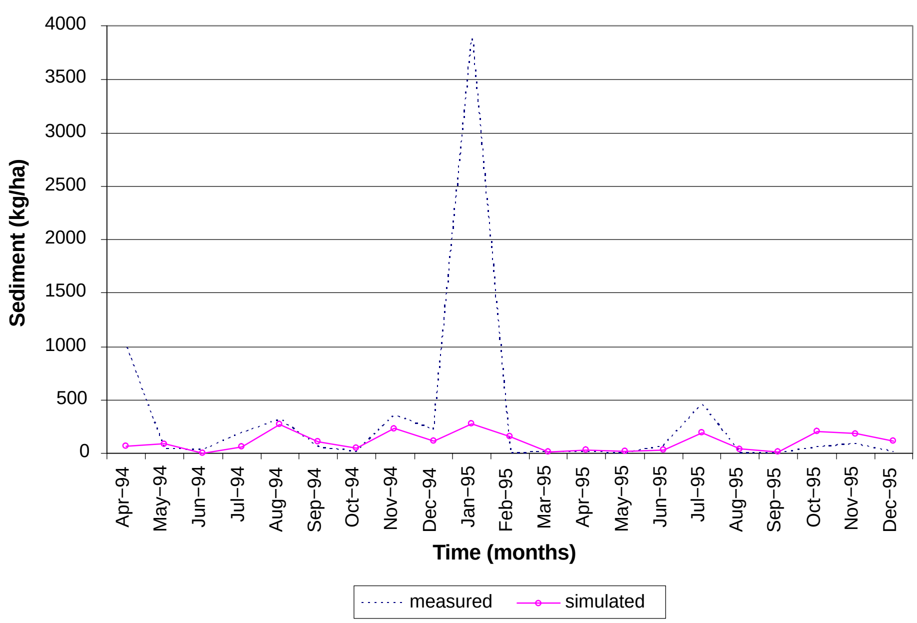

Figure 3. Time series plot of measured and simulated monthly sediment loading (kg/ha) during the calibration period (April, 1994−1995).

Table 6. Statistical results comparing measured and simulated sediment loading at station 2A.

Measurement	No. of Samples	r	r^2	R^2 (Nash−Sutcliffe)	RMS (kg/ha)
Calibration period (April, 1994−1995)					
Monthly sediment	20	0.31	0.1	0.05	229.9
Validation period (1996−1997)					
Monthly sediment	24	0.43	0.19	0.11	402.1
Both periods (April, 1994−1997)					
Yearly sediment	4	0.96	0.91	0.90	659.0

loading (999 kg/ha, fig. 3) in April 1994 was considered to be due to cows wandering across the stream, thus being a part of the natural watershed. However, SWAT was unable to simulate such an occurrence. Therefore, the data point for April 1994 was not considered an outlier and was included in the statistical analysis (table 6). During the calibration period, the r, r^2, and R^2 values (0.31, 0.1, and 0.05, respectively) indicate poor model performance in describing monthly sediment yield. The time series plot of the measured and simulated monthly sediment loading during validation is shown in figure 4. Overall, the monthly simulation results for sediment yield during the validation period are relatively poor, with low r and R^2 values of 0.43 and 0.11 (table 6), respectively. The poor predictions occur for the most part in 1996, an extremely wet year that also created problems for stream flow predictions (Chu and Shirmohammadi, 2004). The poor sediment yield might therefore be attributed to the inability of the model to accurately predict flow during unusually wet hydrologic years. Similar poor predictions were reported by Kirsch (2000) and Kirsch et al. (2002) in southern Wisconsin.

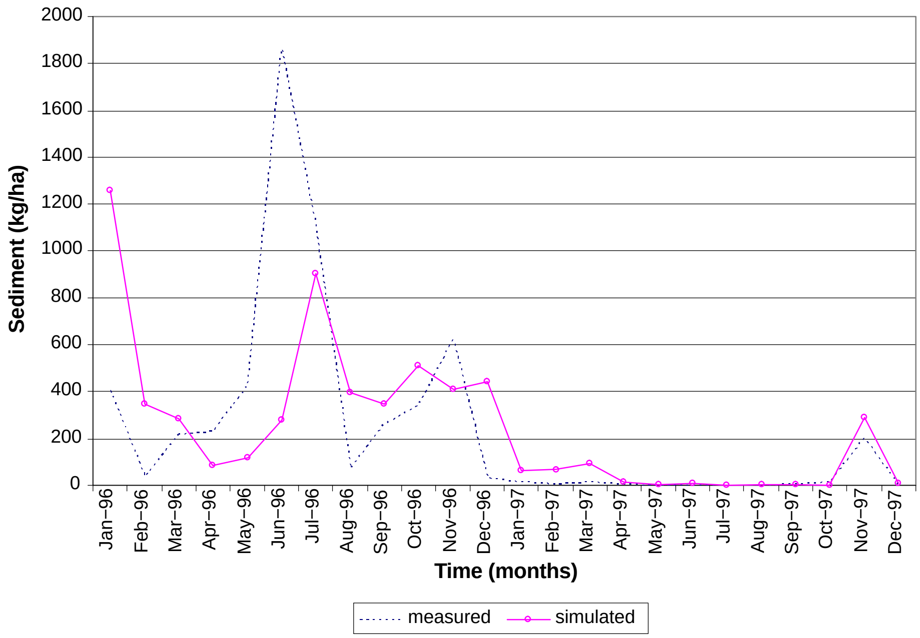

Figure 4. Time series plot of measured and simulated monthly sediment loading (kg/ha) during the validation period (1996−1997).

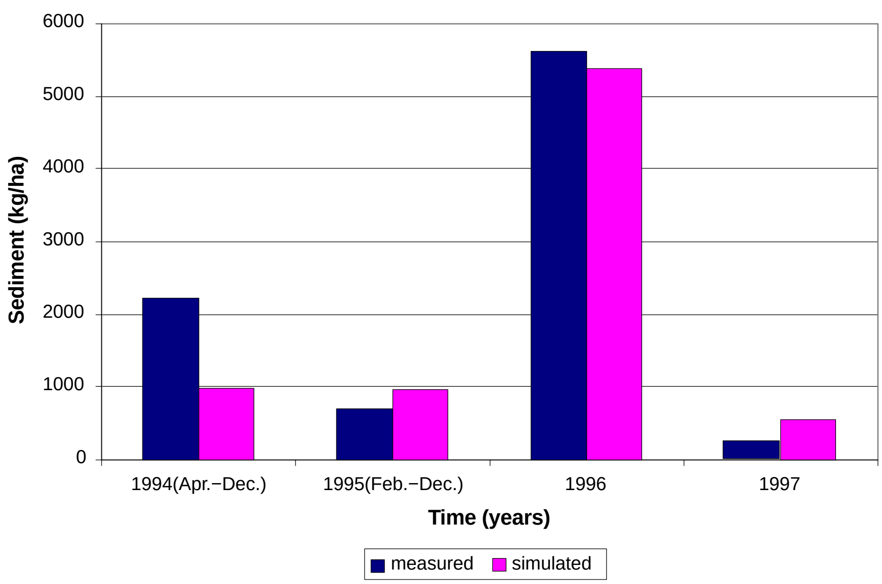

Figure 5. Time series plot of measured and simulated yearly sediment loading at station 2A.

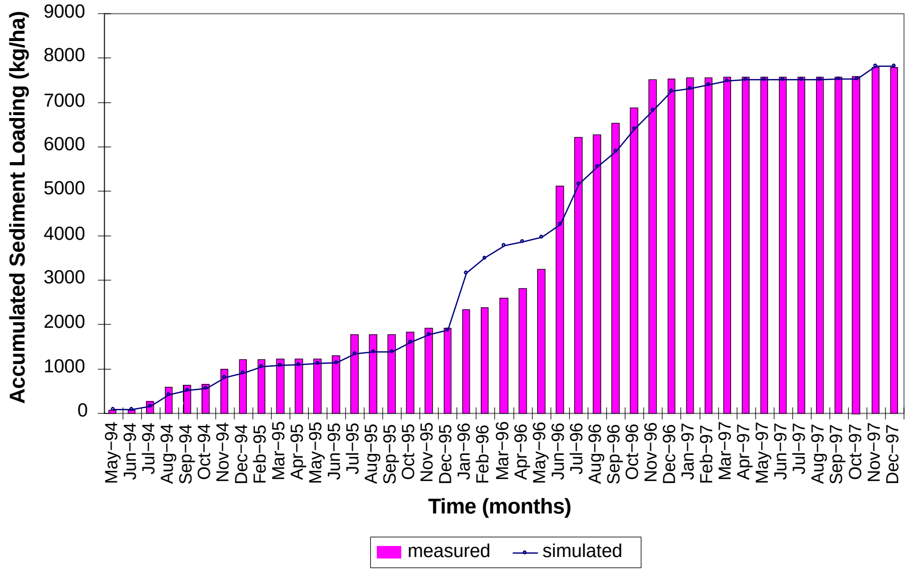

Figure 6. Time series plot of monthly measured and simulated cumulative sediment (kg/ha) at station 2A.

Despite poor predictions of monthly sediment loading, the predicted annual sediment yields agree very well with measured data (fig. 5). The r, r^2, and R^2 values of 0.96, 0.91, and 0.90 (table 6), respectively, display strong agreement between yearly predictions and measurements. Further validation was made to compare the time series plot of cumulative monthly sediment loading. Figure 6 represents the accumulation of simulated and measured monthly sediment yield from May 1994 to 1997 (excluding two extremes in 1994 and 1995). The cumulative simulated sediment loading at the end of years 1995 and 1997 shows only 2.2% and 0.3% relative error, respectively, compared to measured sediment yield, which indicates very good model performance for annual prediction. These results are similar to those from the study conducted by Srinivasan et al. (1998). It should be noted that SWAT, like most deterministic models, is unable to simulate some unexpected occurrences, such as animals stepping into the stream, which may cause rapid elevation of sediment concentration.

NUTRIENTS

Figure 7 presents a time series plot of the model's prediction of monthly nitrate loadings compared with the measured data after adjustment for the groundwater inflow contributions during calibration (April 1994 through December 1995). The trend of simulation seems to match the measured data reasonably well, except for large discrepancies in the months of January and November 1995. This could be partially attributed to the underestimated stream flow by the model in both months. The statistical results of the model's performance in nitrate prediction during the calibration and validation periods are summarized in table 7. The relatively low r, r^2, and R^2 values (0.52, 0.27, and 0.16, respectively) indicate a poor simulation of monthly nitrate loadings during the calibration period.

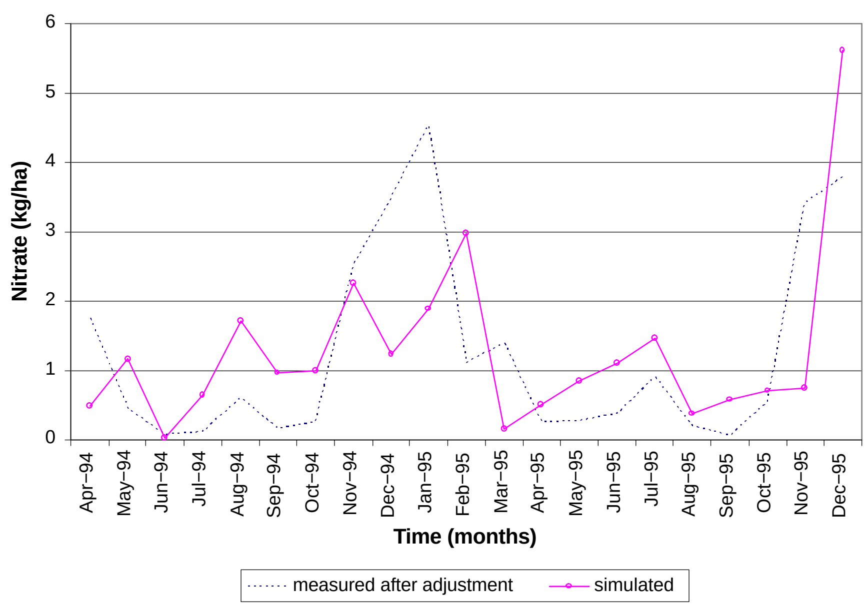

Figure 7. Time series plot of measured and simulated monthly nitrate at station 2A during the calibration period (April, 1994−1995).

Table 7. Statistical results comparing measured and simulated NO_3−N at station 2A after adjustment to the subsurface flow contribution from outside the watershed.

Measurement (adjusted)	No. of Samples	r	r^2	R^2 (Nash−Sutcliffe)	RMS (kg/ha)
Calibration period (April, 1994−1995)					
Monthly NO_3−N	21	0.52	0.27	0.16	1.27
Validation period (1996−1999)					
Monthly NO_3−N	47	0.61	0.38	0.36	1.53
Both periods (1994−1999)					
Yearly NO_3−N	6	0.98	0.96	0.90	2.22

Figure 8 shows the time series plot of monthly observed and simulated nitrate loadings during validation (1996−1999). The simulation displays acceptable correspondence with the measured data, except for extreme flow events in January 1996, January 1999, and October 1999. The regression analysis performed by excluding the deviation of January 1999 represented an improved model simulation, considering the slope of 0.37, r^2 of 0.38, and R^2 of 0.36 (table 7) for validation as compared to the low r^2 of 0.27 and R^2 of 0.16 for calibration. Despite poor performance in predicting monthly nitrate loadings, the yearly comparison showed a strong agreement (fig. 9). Statistical measures summarized in table 7 confirm the graphical presentation by the high r, r^2, and R^2 values (0.98, 0.96, and 0.9, respectively), which indicate great success in prediction of annual nitrate loadings.

The validation results of monthly ammonia loading are presented in figure 10. The time series plot of simulated monthly NH_4−N loading seems to follow most of the trend of measured data, except in January and February 1999 (fig. 10). The ammonia concentrations of these months were much higher than the rest of months. Field investigation

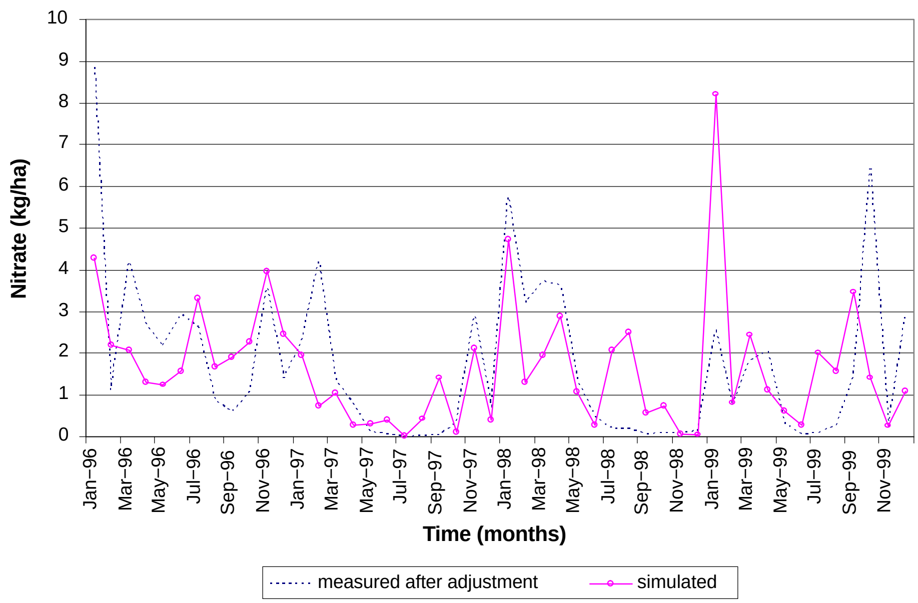

Figure 8. Time series plot of measured and simulated monthly nitrate at station 2A during the validation period (1996−1999).

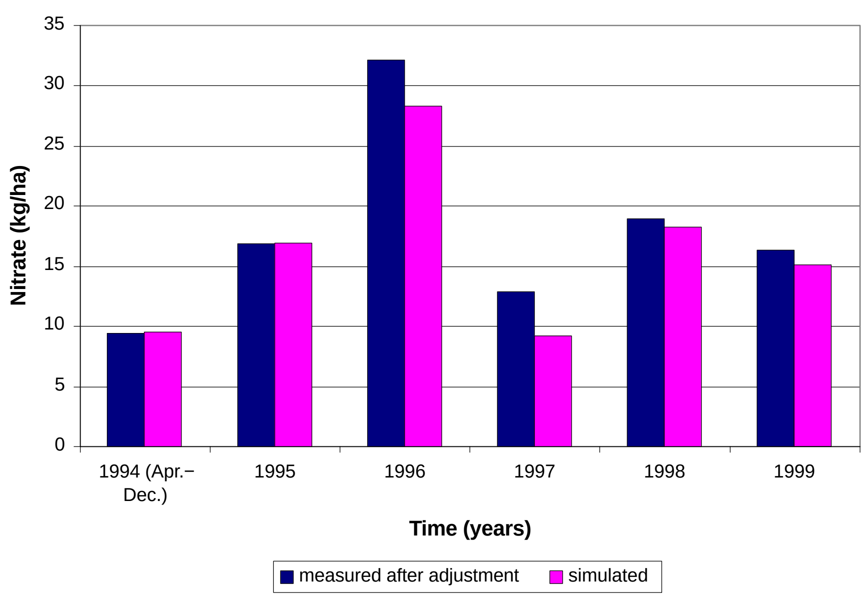

Figure 9. Time series plot of measured and simulated yearly nitrate loading at station 2A.

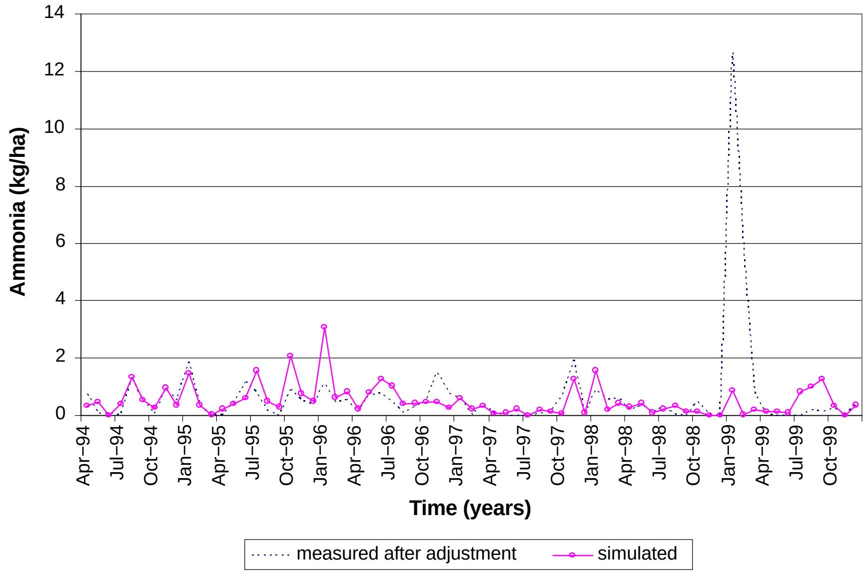

Figure 10. Time series plot of measured and simulated monthly NH_4−N loading at station 2A.

Table 8. Statistical results comparing measured and simulated data (NH_4−N, TKN, and TP) at station 2A after adjustment to the subsurface flow contribution from outside the watershed.

Measurement (adjusted)	No. of Samples	r	r^2	R^2 (Nash−Sutcliffe)	RMS (kg/ha)
Validation period (April, 1994−1999)					
Monthly NH_4−N	67	0.62	0.38	−0.05	0.45
Monthly TKN	67	0.63	0.40	0.15	1.94
Monthly TP	67	0.62	0.38	0.08	0.59
Validation period (1994−1999)					
Yearly NH_4−N	6	0.89	0.80	0.19	1.71
Yearly TKN	6	0.81	0.66	−0.56	13.43
Yearly TP	6	0.91	0.83	0.19	2.08

indicated that ammonium (oxidized to nitrate eventually) based deicer application on the county road in winter may have caused such abnormally high concentration in the stream. These data from the unexpected occurrences were treated as outliers. Statistical results for NH_4−N validation are listed in table 8. Although there is a linear relationship (r = 0.62) between the simulated and measured monthly NH_4−N loadings, the R^2 value of −0.05 indicates a poor performance by the model. However, the simulation of annual NH_4−N loadings presents a much better agreement with measured data, as shown in figure 11 and table 8.

Figure 12 presents the time series plot of simulated and measured monthly TKN loadings during the validation period (1994−1999). Data indicate that the model underestimated TKN loading for most of the time during the entire validation period. Underestimation of TKN may be attributed to the model's underprediction of organic nitrogen because simulated TKN is the summation of simulated ammonia and organic nitrogen. Statistical results of measured and simulated monthly TKN (excluding two extremes in January 1995 and 1999) and yearly comparisons are shown in table 8. Both monthly and yearly statistics indicate that the model performed poorly in predicting organic nitrogen. It should be noted that severe storms of 1995 and 1999 were not

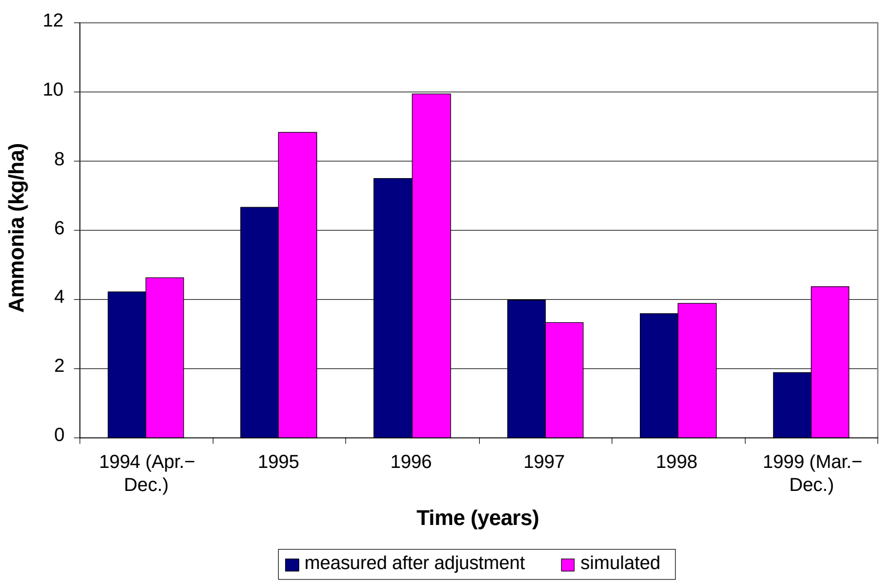

Figure 11. Time series plot of measured and simulated yearly NH_4−N loading at station 2A.

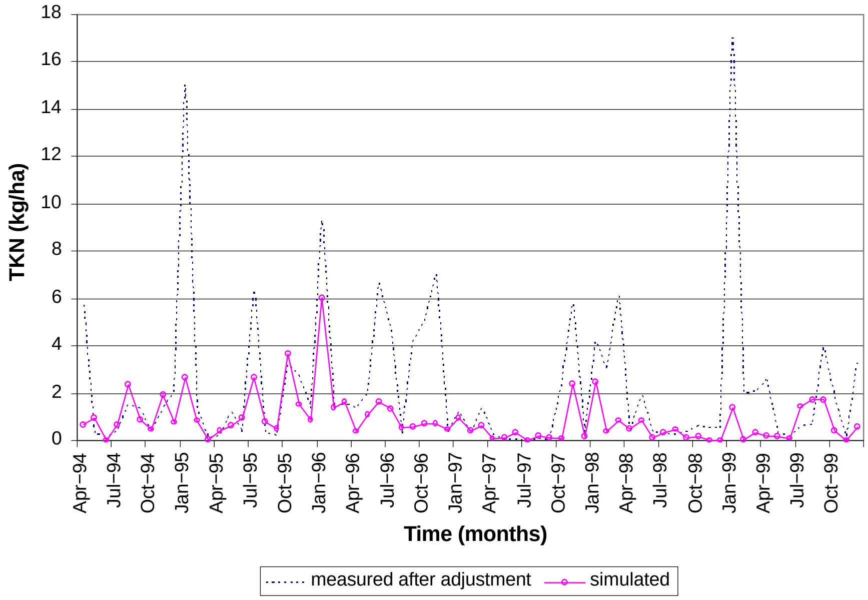

Figure 12. Time series plot of measured and simulated monthly TKN loading at station 2A.

properly simulated by the model due to inherent weakness in the SCS curve number method used in the model. As a result, the model underestimated flow, sediment, and nutrients.

The time series plot of measured and simulated soluble phosphorus during the calibration period (April 1994 through 1996) is shown in figure 13. As with the flow and nitrate data, January 1995 created some problem for soluble phosphorus prediction. The statistics listed in table 9 do not show much of strength for the model's performance, considering a negative R^2 value of −0.08. Figure 14 indicates satisfactory correspondence of simulated soluble phosphorus with measured data, except for a jump in November 1997 during the validation period. The concentration of soluble phosphorus in November 1997 was abnormally higher than in the rest of months. This datum was excluded from the statistical analysis as an outlier. After eliminating the November 1997 datum, the R^2 value of 0.64 (table 9) confirms a reasonable performance by the model. In addition, the yearly simulation of soluble phosphorus displays a better agreement with the measured data than monthly predictions (fig. 15). The statistics in table 9 further indicate good performance by the model in simulating annual loads.

The validation of total phosphorus was performed after the calibration of soluble phosphorus was completed. Figure 16 shows simulations of monthly total phosphorus (soluble phosphorus plus organic phosphorus) loadings compared with measured data for the validation period (April 1994 through December 1999). The time series plot indicates a poor simulation, mostly attributed to the poor prediction of organic phosphorus. Statistical measures calculated by removing two extremes (January 1995 and November 1997) show only marginal model performance of monthly TP, with an R^2 value of 0.08 (table 8). However, the simulation of yearly TP suggested a slightly better model performance, with r, r^2, and R^2 values of 0.91, 0.83, and 0.19, respectively (table 8).

In conclusion, despite some better monthly nutrient predictions reported by Saleh et al. (2000) and Santhi et al.

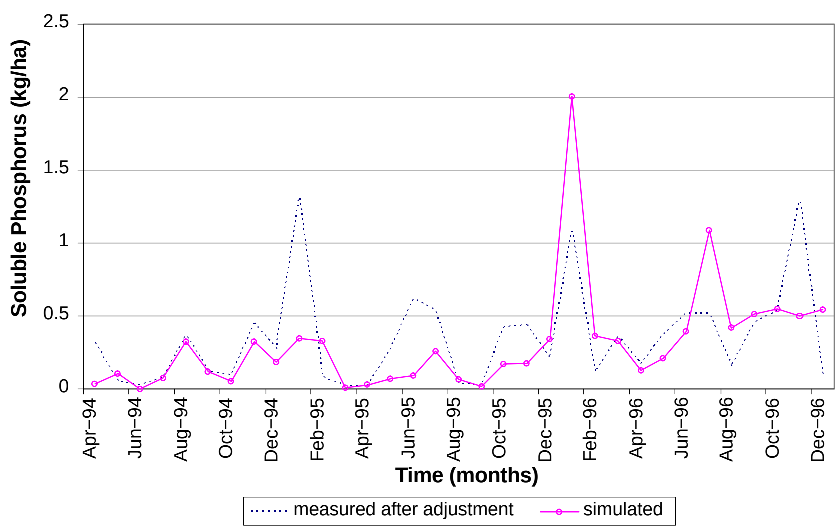

Figure 13. Time series plot of measured and simulated monthly soluble phosphorus at station 2A during the calibration period (April, 1994−1996).

Table 9. Statistical results comparing measured and simulated soluble phosphorus at station 2A after adjustment to the subsurface flow contribution from outside the watershed.

Measurement (adjusted)	No. of Samples	r	r^2	R^2 (Nash−Sutcliffe)	RMS (kg/ha)
Calibration period (April, 1994−1996)					
Monthly soluble P	32	0.62	0.39	−0.08	0.30
Validation period (1997−1999)					
Monthly soluble P	35	0.81	0.65	0.64	0.20
Both periods (1994−1999)					
Yearly soluble P	6	0.93	0.87	0.70	0.88

(2001), SWAT performed poorly in predicting monthly nutrient loadings in the Piedmont physiographic region of Maryland. However, SWAT was capable of simulating annual loadings of nutrients with good accuracy. The lack of detailed information on fertilization (quantity and timing) may have posed some difficulty in nutrient simulations. In addition, the model's inability to handle unexpected occurrences that may have induced spikes in chemical loadings could have lead to some of the erroneous predictions. For example, cows may have stepped into the stream, excreted waste, and agitated streambed sediment shortly before sampling at the downstream station. Ammonium (oxidized to nitrate eventually) based deicers applied to the county road in winter may also have contributed considerable nitrate loadings into the stream that was not accounted for in SWAT simulations. For the monthly NH_4−N loading in January 1999, the big spike may be due to the deicer application. The model performed much better on an annual scale by neglecting those extreme events, especially for nitrate and soluble phosphorus. However, the model seemed to perform only fairly in predicting ammonia nitrogen and organic phosphorus on an annual basis. Organic nitrogen was underpredicted for most of the study period, regardless of the simulation period.

Summary and Conclusion

A conceptual, continuous time, and watershed/large river basin scale, distributed parameter model (SWAT) was applied to a 346 ha watershed with mixed land use in the Piedmont physiographic region of Maryland. Previous studies (Chu et al., 2002; Shirmohammadi et al., 2001) have pointed out that most existing watershed−scale models only consider the subsurface media bounded by the surface topography, thus missing the potential subsurface flow contributions from outside the watershed. Results of water budget analysis by Chu and Shirmohammadi (2004) suggested a considerable groundwater contribution from outside

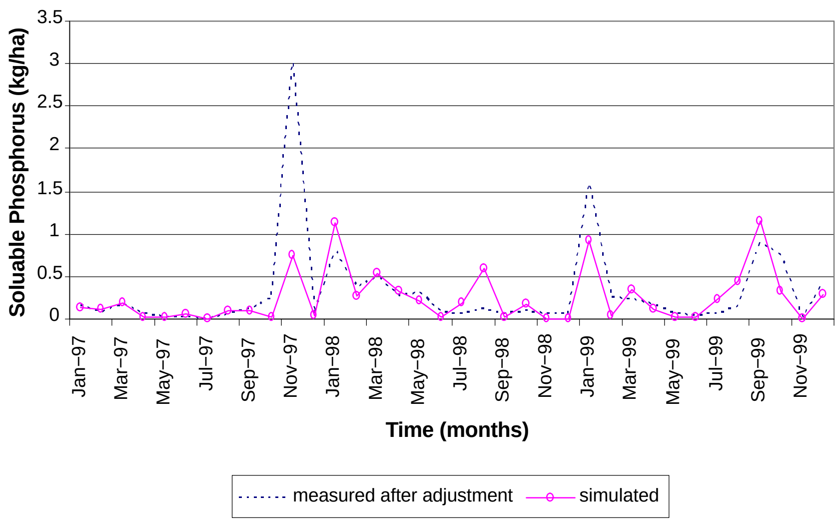

Figure 14. Time series plot of measured and simulated monthly soluble phosphorus at station 2A during the validation period (1997−1999).

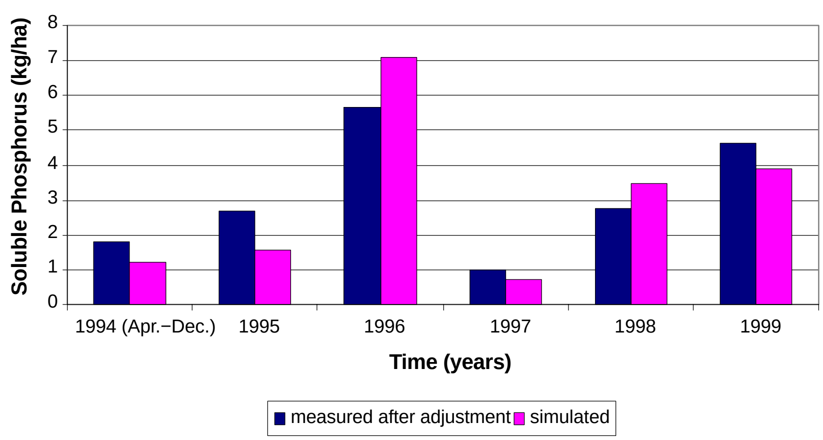

Figure 15. Time series plot of measured and simulated yearly soluble phosphorus loading at station 2A.

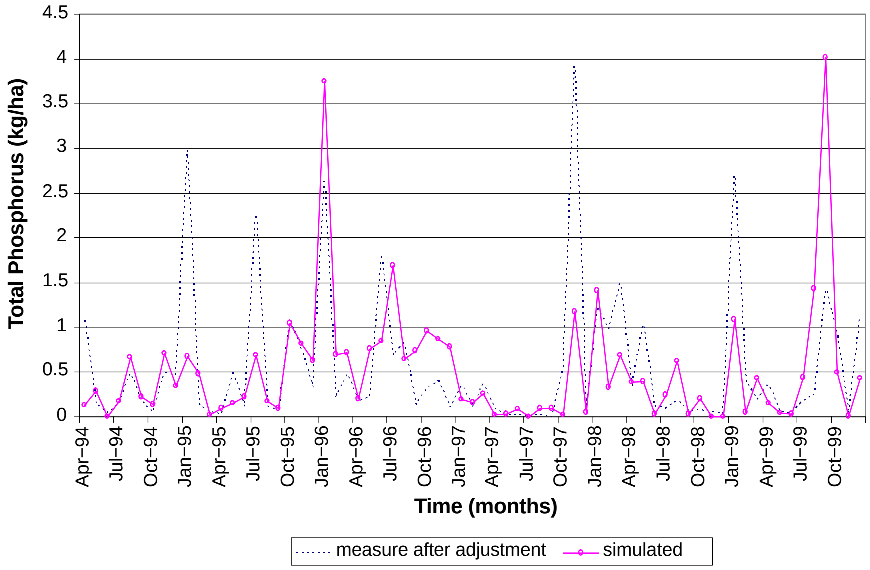

Figure 16. Time series plot of measured and simulated monthly total phosphorus loading at station 2A.

the study watershed. Missing the subsurface flow contributions from outside the watershed may therefore lead to inaccurate predictions of pollutant loading via respective pathways. To evaluate the nutrient component of the SWAT model, all nutrient loadings leaving the watershed were adjusted to subtract the chemical transport via subsurface flow contribution from outside the watershed.

This study concluded that the SWAT model's simulations of monthly sediment loading were poor. However, its performance in predicting annual sediment loading was reasonably good, considering the potential errors within sediment analysis and measurement. Similarly, SWAT performed relatively poorly in predicting monthly nutrient loadings but showed good results in predicting annual nitrate and soluble phosphorus loadings. The model's performance in simulating annual ammonia and organic phosphorus loadings was fair. Organic nitrogen was underpredicted for most of the study period, regardless of the simulation period.

It should be noted again that the SWAT model is not capable of handling unexpected occurrences that induce an increase in sediment or nutrient loadings, and this degrades the model's performance. Overall, SWAT is a reasonable annual predictor of the watershed responses for assessing the impacts of different management systems on water supplies and nonpoint source pollution. It should also be noted that ignoring the subsurface contribution of water and chemicals into the watershed aquifer, especially in small watersheds, could cause significant errors in model prediction. Researchers should be aware of possible subsurface flow contributions from outside of a surface watershed when applying hydrologic models in regions with abundant groundwater or potential aquifer discharge, as may occur in the Piedmont.

Acknowledgements

We are grateful for NPS−319 funds provided by the U.S. EPA through the Maryland Department of Natural Resources. We also appreciate the generous cooperation of the landowners within the Warner Creek watershed (especially the Warner family), the Soil Conservation District Office in Frederick County, and the Cooperative Extension representative, Ms. Patricia Burdette. We also acknowledge the dedicated fieldwork by Mr. Robert Dixon, Engineering Technician, of the Department of Biological Resources Engineering at the University of Maryland.

References

Angle, J. S., V. A. Bandel, D. B. Beegle, D. R. Bouldin, H. L. Brodie, G. W. Hawkins, L. E. Lanyon, J. R. Miller, W. S. Reid, W. F. Ritter, C. B. Sperow, and R. A. Weismiller. 1986. Best management practices for nutrient uses in the Chesapeake Basin. Bulletin 308. College Park, Md.: University of Maryland, Extension Service of the Chesapeake Basin.

Arnold, J. G., and P. M. Allen. 1996. Estimating hydrologic budgets for three Illinois watersheds. *J. Hydrology* 176(1−4): 57−77.

Arnold, J. G., J. R. Williams, R. H. Griggs, and N. B. Sammons. 1990. *SWRRB: A Basin−Scale Simulation Model for Soil and Water Resources Management.* College Station, Texas: Texas A&M University Press.

Arnold, J. G., P. M. Allen, and G. Bernhardt. 1993. A comprehensive surface−groundwater flow model. *J. Hydrology* 142(1/4): 47−69.

Arnold, J. G., J. R. Williams, R. Srinivasan, and K. W. King. 1996. *SWAT: Soil and Water Assessment Tool.* Temple, Texas: USDA−ARS.

Arnold, J. G., R. Srinivasan, R. S. Muttiah, and J. R. Williams. 1998. Large−area hydrologic modeling and assessment: Part I. Model development. *J. American Water Resources Assoc.* 34(1): 73−89.

ASCE. 2000a. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. Artificial neural networks in hydrology: I. Preliminary concepts. *J. Hydrologic Eng.* 5(2): 115−123.

ASCE. 2000b. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. Artificial neural networks in hydrology: II. Hydrologic applications. *J. Hydrologic Eng.* 5(2): 124−137.

Bagnold, R. A. 1977. Bedload transport in natural rivers. *Water Resources Research* 13(2): 303−312.

Bingner, R. L., J. Garbrecht, J. G. Arnold, and R. Srinivasan. 1997. Effect of watershed subdivision on simulation runoff and fine sediment yield. *Trans. ASAE* 40(5): 1329−1335.

Brown, L. C., and T. O. Barnwell, Jr. 1987. The enhanced water quality models QUAL2E and QUAL2E−UNCAS documentation and user manual. EPA document EPA/600/3−87/007. Athens, Ga: USEPA.

Burdette, P. A. 1996. Personal conversion and open project files. Walkersville, Md.: Monocacy Watershed Project Demonstration Office.

Chapra, S. C., 1997. *Surface Water−Quality Modeling.* New York, N.Y.: McGraw−Hill.

Chesapeake Bay Program. 1988. Baywide nutrient reduction strategy. Annapolis, Md.: Chesapeake Bay Program.

Chu, T. W., and A. Shirmohammadi. 2004. Evaluation of the SWAT model's hydrology component in the Piedmont physiographic region of Maryland. *Trans. ASAE* 47(4): 1057−1073.

Chu, T. W., A. Shirmohammadi, H. Montas, and T. Sohrabi. 2002. Modeling watershed nonpoint−source pollution in Piedmont physiographic region using SWAT. ASAE Paper No. 022040. St. Joseph, Mich.: ASAE.

Duigon, M. T., and J. R. Dine. 1987. Water resources of Frederick County, Maryland. Maryland Geological Survey Bulletin 33, 23−25. Baltimore, Md.: Maryland Department of Natural Resources.

Gianessi, L. P., H. M. Peskin, and G. K. Young. 1981. Analysis of national water pollution control policies: A national network model. *Water Resources Research* 17(4): 796−801.

Houser, J. B., and L. M. Hauck. 2002. Analysis of the in−stream water quality component of SWAT (Soil Water Assessment Tool). In *Proc. Conference on Total Maximum Daily Load (TMDL) Environmental Regulations*, 52−55. A. Saleh, ed. ASAE Publication No. 701P0102. St. Joseph, Mich.: ASAE.

Kirsch, K. J. 2000. Predicting sediment and phosphorus loads in the Rock River basin using SWAT. ASAE Paper No. 002175. St. Joseph, Mich.: ASAE.

Kirsch, K. J., A. Kirsch, and J. G. Arnold. 2002. Predicting sediment and phosphorus loads in the Rock River basin using SWAT. *Trans. ASAE* 45(6): 1757−1769.

Leonard, R. A., and R. D. Wauchope. 1980. Chapter 5: The pesticide submodel. In *CREAMS: A Field−Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems*, 88−112. W. G. Knisel, ed. USDA Conservation Research Report No. 26. Washington, D.C.: USDA.

McElroy, A. D., S. Y. Chiu, J. W. Nebgen, et al. 1976. Loading functions for assessment of water pollution from nonpoint sources. EPA 600/2−76−151. Athens, Ga.: USEPA.

Nash, J. E., and J. V. Sutcliffe. 1970. River flow forecasting through conceptual models: Part I. A discussion of principles. *J. Hydrology* 10(3): 282−290.

Saleh, A., J. G. Arnold, P. W. Gassman, L. M. Hauck, W. D. Rosenthal, J. R. Williams, and A. M. S. McFarland. 2000. Application of SWAT for the upper North Bosque River watershed. *Trans. ASAE* 43(5): 1077−1087.

Santhi, C., J. G. Arnold, J. R. Williams, W. A. Dugas, R. Srinivasan, and L. M. Hauck. 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. *J. American Water Resources Assoc.* 37(5): 1169−1188.

Santhi, C., J. R. Williams, W. A. Dugas, J. G. Arnold, R. Srinivsan, and L. M. Hauck. 2002. Water quality modeling of Bosque River watershed to support TMDL analysis. In *Proc. Conference on Total Maximum Daily Load (TMDL) Environmental Regulations*, 33−43. A. Saleh, ed. ASAE Publication No. 701P0102. St. Joseph, Mich.: ASAE.

Searing, M. L., and A. Shirmohammadi. 1994. The design, construction, and analysis of a GIS database for use in reducing nonpoint−source pollution on an agricultural watershed. ASAE Paper No. 943551. St. Joseph, Mich.: ASAE.

Shirmohammadi, A., K. S. Yoon, and W. L. Magette. 1997. Water quality in a mixed land−use watershed − Piedmont region in Maryland. *Trans. ASAE* 40(6): 1563−1572.

Shirmohammadi, A., T. W. Chu, H. Montas, and T. Sohrabi. 2001. SWAT model and its applicability to watershed nonpoint−source pollution assessment. ASAE Paper No. 012005. St. Joseph, Mich.: ASAE.

Spruill, C. A., S. R. Workman, and J. L. Taraba. 2000. Simulation of daily and monthly stream discharge from small watersheds using the SWAT model. *Trans. ASAE* 43(6): 1431−1439.

Srinivasan, R., T. S. Ramanarayanan, J. G. Arnold, and S. T. Bednarz. 1998. Large−area hydrologic modeling and assessment: Part II. Model application. *J. American Water Resources Assoc.* 34(1): 91−101.

USDA−SCS. 1960. Soil survey Frederick County, Maryland. Series 1956, No. 15. Washington, D.C.: U.S. Govt. Printing Office.

USDA−SCS. 1989. The second RCA appraisal: Analysis of conditions and trends. Washington, D.C.: U.S. Govt. Printing Office.

USDA−SCS. 1990. Maryland Chesapeake Bay Cooperative River Basin Study. Washington, D.C.: USDA.

USEPA. 1991. Watershed monitoring and reporting for section 319 national monitoring program projects. Washington, D.C.: USEPA, Office of Water, Assessment and Watershed Protection Division.

USEPA. 1998. National water quality inventory: 1996 report to congress. EPA 841/R−97/008. Washington, D.C.: USEPA, Office of Water.

Vandenberghe, V., A. Van Griensven, and W. Bauwens. 2001. Sensitivity analysis and calibration of the parameters of ESWAT: Application to the River Dender. *Water Science and Tech.* 43(7): 295−301.

Williams, J. R. 1975. Sediment routing for agricultural watersheds. *Water Resour. Bull.* 11(5): 965−974.

Williams, J. R. 1990. The erosion productivity impact calculator (EPIC) model: A case history. *Phil. Trans. Royal Soc. London* 329: 421−428.

Williams, J. R. 1995. Chapter 25: The EPIC model. In *Computer Models of Watershed Hydrology*, 909−1000. V. P. Singh, ed. Highlands Ranch, Colo.: Water Resources Publications.

Williams, J. R., and R. W. Hann. 1978. Optimal operation of large agricultural watershed with water quality constraints. Tech. Report No. 96. College Station, Texas: Texas A&M University, Texas Water Resources Institute.

Williams, J. R., J. G. Arnold, R. Srinivasan, and T. S. Ramanarayanan. 1998. APEX: A new tool for predicting the effects of climatic changes and CO_2 changes on erosion and water quality. In *Modeling Soil Erosion by Water: NATO−ASI Global Change Series*, 441−449. J. Boardman and D. Favis−Mortlock. eds. Heidelberg, Germany: Springer−Verlag.